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Modeling the Probability of Surface Artificialization in Zêzere Watershed (Portugal) Using Environmental Data

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Abstract: The land use and land cover (LUC) of the Zêzere watershed (Portugal) have undergone major changes in recent decades, with the increase of artificial surfaces. This trend is quantified in some studies, but the probability of the increase of this type of LUC, nor the places where the next transitions or land use/cover changes (LUCC) for artificial surfaces will have high probability of occurrence has not yet been assessed. This research presents an evaluation of these two aspects, by means of bivariate statistical models (fuzzy logic and information value) and environmental data. The artificialization probability by sectors within the same watershed is also evaluated, to further understand which areas will require greater attention, taking into account the environmental conditions favorable to the occurrence of this process and bearing in mind the conditions under which this process took place in the past. The results obtained using these models were assessed independently, through curves of success, noting that the modeling through the fuzzy gamma presents slightly better efficiency in determining the probability of artificialization surfaces in the study area. The area with the highest probability of artificialization is mostly located in the SW of this watershed, but high probabilities are also present in the upstream sector, being those areas that require further preventive measures once they have influence on the water quality and quantity in the main reservoirs of this watershed.

Keywords: LUC; LUCC; artificial surfaces; fuzzy logic; information value; spatial analysis; water quality

1. The Artificialization of Surfaces and Their Assessment

Urban growth has been evaluated in different territories around the world, considering the spatiotemporal aspect, as well as the factors that induced it [1–6]. Other studies have emerged in the context of land use and land cover changes (LUCC) to assess where the soils are being converted into artificial surfaces [7–11], especially when there is loss of soils essential for the development of agricultural practices, or the conversion of forest areas. These processes have multiple socio-economic and environmental impacts [12–16]. In this sense, the determination of driving forces (socio-economic, environmental, or other) that are the cause of LUCC is fundamental to understand the factors that induced them and for the creation of measures aimed at the sustainability of land use [15,17]. Some studies demonstrating the links between driving forces and LUCC have appeared recently, also quantifying how much each factor represents to the observed changes [13,18–22].

In Portugal, studies addressed the impacts of LUCC in the environment, in particular the major transitions of land use and land cover (LUC) resulting from deforestation and their contribution to emissions and removals of CO_2 [23], or in water bodies [17,24,25].

The evaluation of disturbances caused by LUCC in water availability (quantity and quality) are also essential for a sound land use planning [17], particularly in places where there was already degradation of this natural resource by the occurrence of certain harmful events, e.g., forest fires [26].

Urban growth can be considered a negative factor on water availability, particularly where this causes water stress [17]. In this context it is desirable to minimize the artificialization in the neighborhood of important water reservoirs used to supply the populations and their activities, namely within the influence area of water catchment towers.

The artificialization of surfaces has been quantified in the Portuguese territory based on cartography produced in recent years (LUC maps of Portugal, Landyn maps, and CORINE Land Cover—CLC). Data consistency increased a great deal with the most recently reviewed and published datasets [8,27,28].

However, so far there are no estimates of the possible increase in this type of LUC (in area), or the soils which will most likely be occupied or suffer LUCC for this type of LUC. In hydrographic basins the increase of this type of LUC has negative impacts, especially in the increase of surface runoff and also in the increase of physical and chemical substances of anthropic origin that are drained to the water bodies, causing their degradation [17].

The evaluation of urban growth has been based on methodologies using Geographic Information Systems (GIS) and remote sensing tools for the assessment of LUCC [1,3,5,29]. These tools for the collection, processing, and analysis of geographic information (GI) allow more detailed analysis of LUCC and the monitoring of natural or anthropogenic processes [30] that occur in the territories (e.g., artificialization surfaces).

For the evaluation of the LUCC, different methodologies have been used, especially the cellular automata model and artificial neural networks, with good results in the estimation and representation of land cover dynamics [6,31–34]. In the estimation of future LUCC, the probabilistic cellular automata-Markov model has been used in several studies [6,35–38].

Many studies have determined the probability of occurrence of a phenomenon in the future (e.g., landslides, risk of forest fire, floods, etc.) [39–42] based on the conditions observed in the past that caused certain phenomena in a certain place. These methodologies have a strong statistical component, differing only in the integration of the respective variables and method of calculation (e.g., bivariate methods and logistic regression). These factors can provide different results and, consequently, different interpretations. Thus, the methods used for the validation of results are essential to understand what is the best method for modeling a given phenomenon [42].

Some methodologies for validating results have emerged, including the modeling of the probability of occurrence of a natural phenomenon with verified occurrences and, thus, allowing the verification of the final results (through the intersection of GI) if the same occurrences fall on the areas with the highest probability of occurrence. Another option is to use part of the dependent variable for modeling and another part to validate the results obtained (random partition). These methods allow the development of success or prediction curves [43] and receiver operating characteristic (ROC) [44,45], and to quantify their robustness for modeling.

2. Main Objectives

This research aims to test two bivariate statistical models for the identification of areas with higher probability of surface artificialization in the Zêzere watershed (Portugal), bearing in mind the increase verified in the last two decades.

The information used is essentially environment-related data, once we considered in this study that socio-economic conditions remain constant, so this information was not part of the model.

The validation of results will take place with information of LUC, namely information about artificial surfaces for two different times: 1990 and 2012. The information of the first year will be used to determine the areas with highest probability of artificialization and the information of the last year will serve to validate the results. We also considered an intermediate date (2000) for verification of the probability of surface artificialization, obtained with data from 1990, being that this data is complementary for the assessment of the validation performed with 2012 data.

Another goal of this study is to determine the differences between the two models in different locations (sectors) within the watershed, in order to quantify and understand the differences between all sectors. Special attention is taken in assessing which are the most important independent variables for determining the probability of artificialization for this territory.

3. Research Area

The study area is the Zêzere watershed (Portugal) (Figure 1). This watershed has an area of 502,278.4 ha, and includes one of the main drinking water reservoirs (Castelo de Bode) in Continental Portugal. The surface artificialization in 1990 was approximately 1.2% of the total area of the watershed, but in the last two decades it has increased approximately 0.5% (according to data from CLC of 1990 and 2012), especially in the vicinity of water bodies. This factor can induce water stress within this watershed, namely decreasing water quality and increasing water treatment costs [17,46].

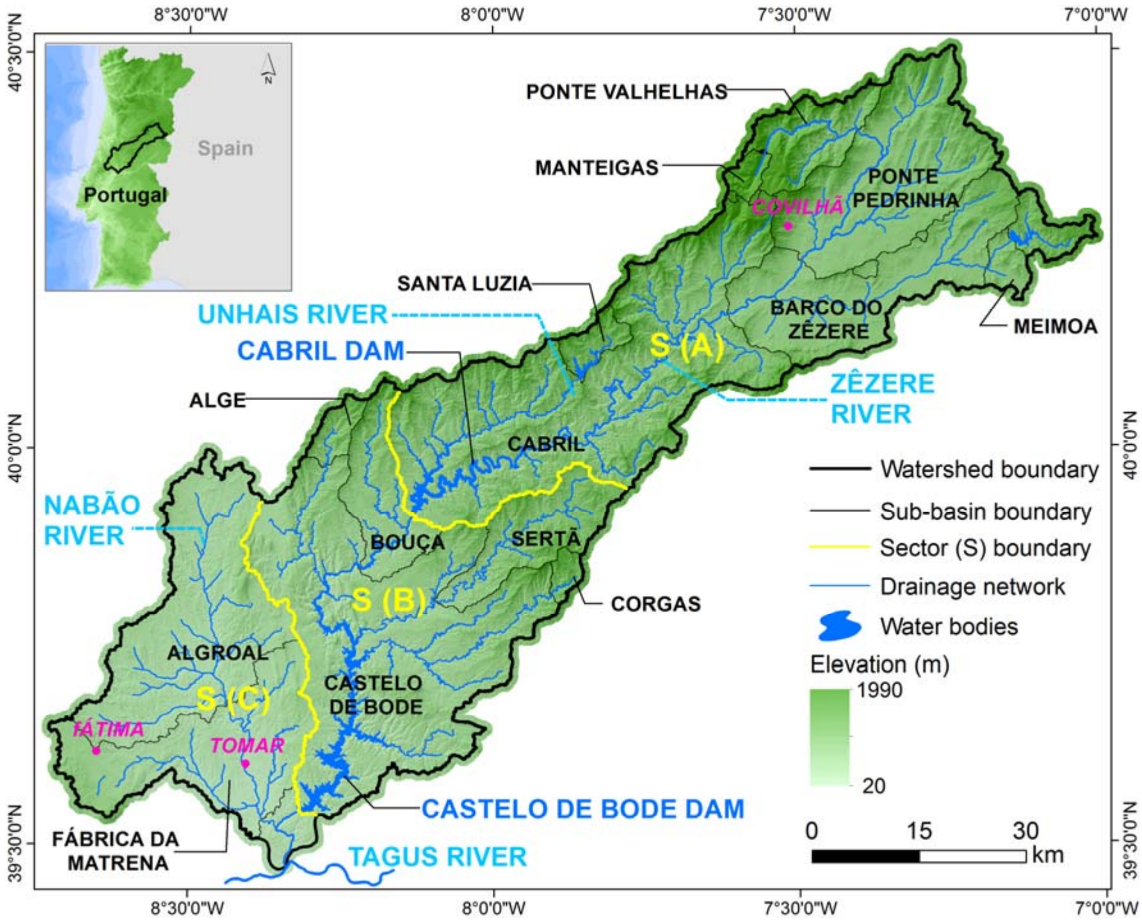

Figure 1. Zêzere watershed (study area).

The watershed was divided into three sectors (Figure 1): two of them based on the location of the main reservoirs (A and B) and one based on the sub-basins without reservoirs (C). The objective of this division areas is to assess the differences in the probability of artificialization: initially within the watershed, considered as a whole, with the selected statistical models, and later to evaluate and differentiate, spatially, this probability between the different watershed sectors and their behavior when compared to the whole watershed results.

In this watershed, since 1990, the artificial surfaces areas increased, particularly in the sub-class discontinuous urban fabric (Table 1). This increase in dispersed artificial surfaces carries greater economic and financial burden, associated in particular with the construction of basic infrastructures (roads, sewage systems, drinking water, power supply, etc.). Here there are also records of environmental disturbances, particularly at the level of domestic waste and water treatment, confirming a deficiency in this area.

Table 1. Areas occupied by artificial surfaces (%) in the Zêzere watershed, from 1990 to 2012.

LUC	1990	2000	2006	2012
Continuous urban fabric	0.02	0.02	0.02	0.02
Discontinuous urban fabric	1.01	1.13	1.15	1.32
Industrial or commercial units	0.06	0.16	0.25	0.24
Road and rail networks and associated land	0.00	0.00	0.01	0.01
Airports	0.01	0.01	0.01	0.03
Mineral extraction sites	0.03	0.05	0.06	0.06
Dump sites	0.01	0.01	0.02	0.03
Construction sites	0.04	0.05	0.01	0.00
Sport and leisure facilities	0.01	0.01	0.01	0.01

In the watershed upstream sector (A) it is located the Estrela mountain (Serra da Estrela). Here the hillsides with slopes exceeding 20% are one of the constraints to urbanization and, thus, the location of major cities and towns is primarily in locations with lower altitude and reduced slope. The Cabril dam is located in this sector of the watershed; an important infrastructure for public water supply.

Sector B comprises the Castelo de Bode reservoir, this area being mainly occupied by scrub and/or herbaceous vegetation associations, resulting mainly from large forest transitions that occurred between 1990 and 2012. This sector also comprises hillsides with slopes exceeding 20%.

The geomorphology of the downstream sector (Sector C) is totally different from the upstream sectors, i.e., the relief is more flat, and was one of the factors that facilitated the urban settlement (e.g., Tomar City). This sector is also characterized by other factors, such as soil characteristics, favorable to the development of agricultural practices, high sun exposure, higher temperature, proximity to water courses, and proximity to railways connecting the area with larger urban areas, like Lisbon, among others. Nevertheless, this is the most relevant sector within the Zêzere watershed once it includes the most relevant water catchment within the Portuguese drinking water supply infrastructure.

The artificial surfaces increase at this watershed occurred in areas very close to the major urban centers within the watershed (Tomar, Fátima, and Covilhã). The analysis of the geographical dispersion of the artificial surfaces (from data of the CLC) found that the new areas have emerged as the expansion of existing ones, particularly on the periphery of the main larger conurbations (Figure 2). It was also found that the largest increase in artificial surfaces occurred until the year 2000, within less than 5 km of the urban centers previously referred.

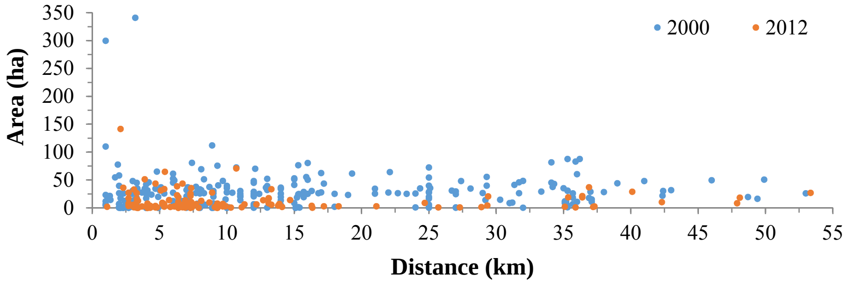

Figure 2. Dispersion of new artificial surfaces. Relation between the distance of centroids of these surfaces (2000 and 2012) to principal urban centers (Tomar, Fátima and Covilhã).

4. Data, Tools, and Methods

4.1. Statistical Methods and Validation

The areas with higher probability of artificialization were determined using fuzzy logic [47] and information value [48] methods. This last methodology was adapted to the study of surface artificialization probability. In these methods it is assumed that a particular phenomenon that occurred in a given territory has a probability to happen in the future under the same conditions under which it occurred in the past [42,49–51].

For the determination of information value, first we calculated a priori and conditional probabilities. This methodology was presented in Meneses and Zêzere et al. [42,52]. After calculating these probabilities, we used the following equation to determine the information value [48]:

$$I_i = Ln\frac{CPji}{Pp} \tag{1}$$

In Equation (1), I_i is the information value; $CPji$ is the conditional probability of surface artificialization on class i of the thematic map j; and Pp is the a priori probability of occurrence of surface artificialization.

In assessing the final probability of surfaces artificialization, i.e., integrate information values of all independent variables, we considered the following equation:

$$I_j = \sum_{i=0}^{n} X_{ij} I_i \tag{2}$$

In Equation (2), I_j is the total information value of pixel j, I_i is the information value of each pixel of each independent variable, n is the number of variables, X_{ij} assumes the value 1 or 0 depending on the presence or not of the variable in the field unit.

The fuzzy logic methodology, developed by Zadeh [53], admits the variation between 0 and 1 (or 0 and 100%) of an existing element in a given set, this being expressed by a fuzzy membership value. According to Bonham-Carter [47], the assignment of values of fuzzy membership to every variable is typically made from the subjective evaluation (expert opinion) of their importance in the model, so it is considered an heuristic method. However, in this study, the fuzzy membership values were assigned objectively to each class of independent variables, i.e., its importance was calculated in proportion to each calculated conditional probability. The maximum value of all of the independent variables was determined and, from this, for each class, the respective fuzzy membership value was calculated as the result of dividing the respective conditional probability by the maximum value found earlier.

Among the various operators for combining fuzzy membership values, we used the fuzzy gamma operator, because this combines two operators [47]: sum and algebraic product. The Fuzzy gamma operator uses the following equation [47]:

$$Fuzzy\ Gamma = \left(1 - \prod_{i=1}^{n}(1-\mu_i)\right)^{y}\left(\prod_{i=1}^{n}\mu_i\right)^{1-y} \tag{3}$$

In Equation (3), μ_i is the fuzzy association values (i = 1, 2, 3, . . . , n) for the variables 1, 2, 3, . . . , n; n corresponds to the number of variables considered, and y the parameter set by the operator.

The geographic information of the artificial surfaces considered in this study is the result of the CLC for the years 1990 and 2012 (level 2), comprising approximately 5978 and 8588 ha, respectively. The GI of the first year (dependent variable) was used for modeling with the methods presented earlier; and the GI for the last year was used for validation of the results, considering in this procedure only the artificial surfaces that have emerged between the two years (approximately 2610 ha). By applying this procedure, we want to know if the artificial surfaces of 2012 coincide with the areas with the highest probability of artificialization obtained by the models previously described.

The process used for the validation of results included the elaboration of success curves and the measurement of the area under the curve (AUC), according to the methodology described by Meneses [42] and Tehrany et al. [43]. This method of validation enables the evaluation of the robustness of the models presented for the determination of artificial surfaces probabilities.

In the analysis of the results the sectors A, B, and C (Figure 1) were distinguished in order to determine the possible differences between the results of the two models on the probability of artificialization surface within the same watershed.

The importance of each independent variable in the process of artificialization for each sector was also determined, in order to understand what the spatial influence of each predisposition factor in the development of this process is. In this procedure the accountability (A_I) and reliability (R_I) indexes [42,54] were determined using Equations (4) and (5). A_I explains how various classes of predisposition factors are relevant in the analysis because they contain artificial surfaces, while R_I depends on the average density of artificial surfaces in classes of predisposition factors most relevant to the development of this process.

$$A_I = \frac{\sum_{i=1}^{n} k}{N} 100 \tag{4}$$

$$R_I = \frac{\sum_{i=1}^{n} k}{\sum_{i=1}^{n} y} 100 \tag{5}$$

In Equations (4) and (5), A_I is the accountability index; R_I is the reliability index; k is the area of artificial surfaces in classes with values of conditioned probabilities superior to a priori probabilities; N is the total area of artificial surfaces; y the area of each class of independent variable with conditioned probability above the a priori probability.

4.2. Data Collection and Tools

The GI themes considered in this research are diversified (Figure 3). Cartography of the Portuguese Environment Agency (soil maps, insolation, humidity, temperature, and precipitation), available online, was used. The LULC considered is the CLC data produced by the Portuguese General Directorate for Territorial Development. Due to the similarity between the spatial geological units and the soil types, we opted to use only this last variable.

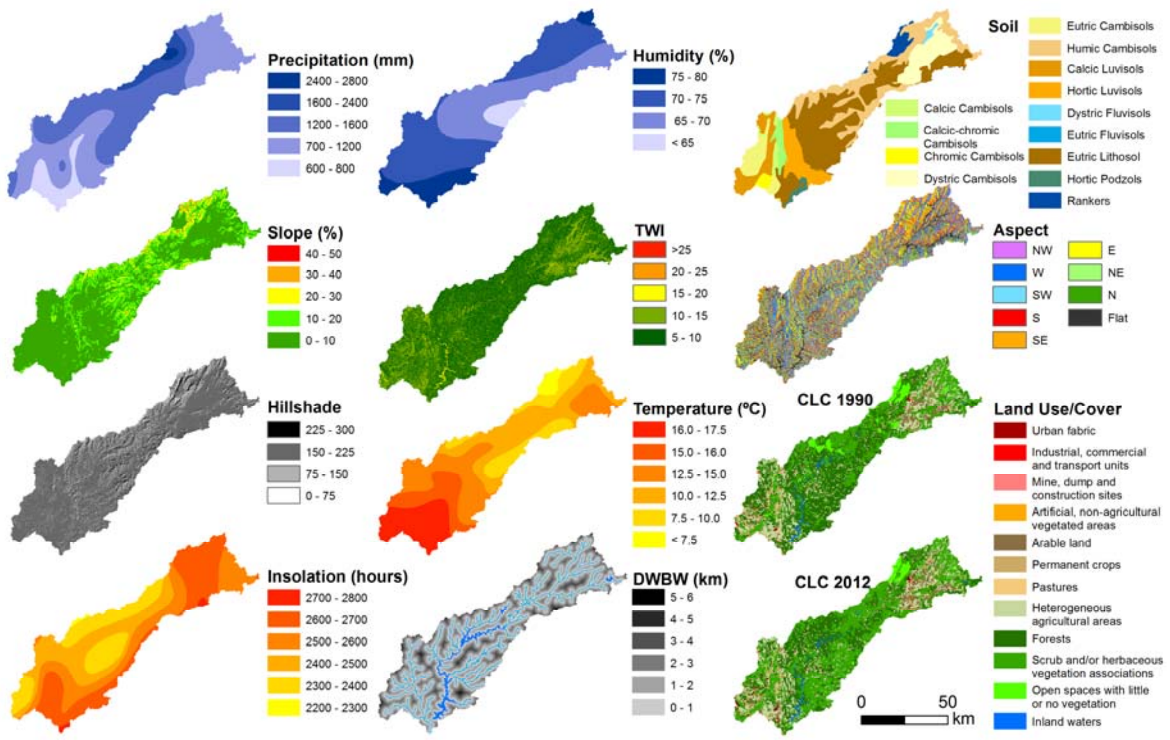

Figure 3. Independent variables used in modeling artificial surfaces and LUC (CLC) in the years 1990 and 2012.

Variables derived from the Digital Elevation Model (DEM) from the GMES RDA project (EU-DEM) made available by the European Environment Agency, were also used, in particular the slope, aspect, and hillshade. These variables derived from the DEM also calculated the topographic wetness index—TWI [55].

In addition to this GI, the distance to water bodies and watercourses (DWBW) was also obtained, to assess the influence of their location on the surface artificialization that occurred over the last two decades, since the vicinity of the main reservoirs in the Zêzere watershed [46] was subject to an increase in housing developments.

All collected GI was harmonized and manipulated in the Geographic Information Systems (GIS), using the software ArcGIS 10.2 and ILWIS 3.4. The GI of the variables in vector structure was converted to raster (pixel 10 × 10 m) for carrying out the various processing procedures. The selection of this resolution was the result of several geoinformation conversion tests, where different modeling resolutions were tested in this research, and it was found that the results of the adopted resolution are similar to those obtained using data with higher resolution. After several vector-to-raster conversions, the resolution considered is the one that allows better results in the determination of artificialization probabilities, since the surface loses a lot of information in the process of generalization that occurs during data conversion, in particular in the conversion of LUC, where small buildings were not considered in the modeling due to the pixel size (e.g., 20 m × 20 m = 400 m^2), and some of the buildings that appeared during the period under evaluation are also not included in the validation process.

For the intersection of the variables presented in Figure 3 we used only ArcGIS 10.2. This software was also used for determining the areas with greater probability of artificialization. On the fuzzification of fuzzy membership values we used the Spatial Data Modeler (ArcSDM), module added to ArcGIS 10.2.

In order to verify that the artificialization surface probabilities obtained from the year 1990 (CLC data) have sequences 10 years later, we also calculated the probabilities for the year 2000. With these results we intended to check the correspondence between the two years (similar odds for the same class of independent variables) so as to enhance the use of the information of 2012 in the context of the models adopted.

5. Results and Analyses

5.1. Conditioned Probabilities of Artificialization Surfaces in the Zêzere Watershed

Each class of independent variables considered in this study presents a different probability of surface artificialization (Table 2). The flat surfaces are those that have a higher probability (higher conditional probabilities) in the variable Aspect, a fact confirmed also in the variable Slope (greater in weak slopes); for hillshade, with records varying between 0 and 300, the most influential is the class 150–200; also with high probability are the surfaces with higher humidity, insolation, and temperature. The distance to water bodies and watercourses is also one factor that conditions the surface artificialization, where the 4–5 km buffer in DWBW has the highest probability (*CPji* AS 1990 in Table 2), due to the total artificial surface included in it. However, the artificial surface is high along water courses (up to 1 km vicinity), revealing a pattern in the preference for these surfaces for the location of infrastructures (housing, industrial complexes, etc.). The Topographic Wetness Index (TWI) reveals that the surfaces with lower values are the ones that have less probability of artificialization.

For calculating the information value, the a priori probability (probability to find artificial surfaces) should be also calculated, which is 0.012. This value results from the division of the total area of artificial surfaces by the total area of each independent variable.

The relationship (coefficient of determination—R^2) between the conditional probabilities obtained from information of artificial surfaces of 1990/2000 is high for most independent variables (Figure 4), with the exception of DWBW, where it was observed a significant increase of artificial surfaces in more distant areas to water bodies and watercourses in the year 2000, given the area occupied by artificial surfaces in 1990. The R^2 between the conditional probabilities of 1990/2012 is also high, with some variables with lower R^2 compared to 1990/2000, such as the Insulation and TWI, but the DWBW highlights with a higher R^2, indicating the greater probability of artificialization in the vicinity of water bodies.

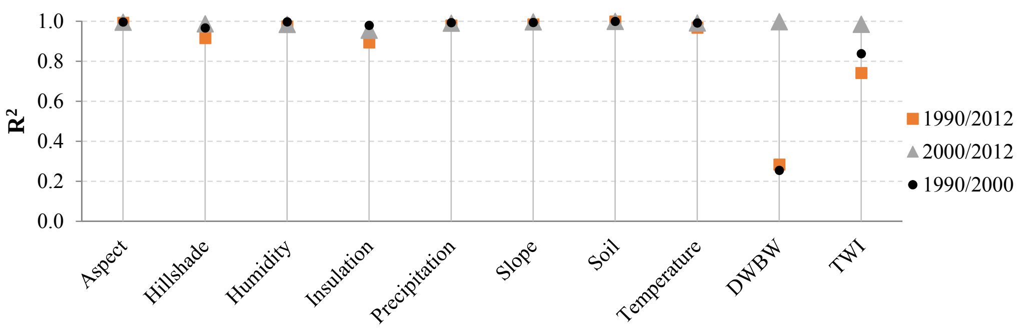

Figure 4. R^2 resulting between conditioned probabilities of artificial surfaces of 1990/2000, 2000/2012, and the total period (1990/2012).

Considering the conditional probabilities of 1990/2000, 2000/2012, and 1990/2012 of all independent variables it was verified that a high correspondence between the results was obtained (R^2 = 0.994, 0.999 and 0.992, respectively).

Table 2. Area of artificial surfaces (AS), conditional probability (*CPji*), information value (IV), and fuzzy membership value (FM) for each class of the independent variables, in the Zêzere watershed.

Variables	Classes	Total Area (ha)	AS 1990 (ha)	AS 2000 (ha)	AS 2012 (ha)	*CPji* (AS 1990)	*CPji* (AS 2000)	*CPji* (AS 2012)	IV (AS 1990)	FM (AS 1990)
Aspect	Northwest	51,549.15	338.96	409.33	482.17	0.007	0.008	0.009	−0.593	0.007
	West	56,574.22	411.9	489.83	549.45	0.007	0.009	0.010	−0.491	0.008
	Southwest	61,918.88	705.13	848.98	967.34	0.011	0.014	0.016	−0.044	0.013
	South	57,996.57	884.72	1050.81	1209.06	0.015	0.018	0.021	0.248	0.017
	Southeast	61,927.05	786.6	953.71	1138.82	0.013	0.015	0.018	0.065	0.014
	East	54,624.12	642.44	787.59	961.53	0.012	0.014	0.018	−0.012	0.013
	Northeast	48,357.44	525.06	657.68	791.94	0.011	0.014	0.016	−0.092	0.012
	North	42,475.03	300.68	379.59	458.83	0.007	0.009	0.011	−0.52	0.008
	Flat	66,855.89	1382.43	1682.28	2028.42	0.021	0.025	0.030	0.552	0.023
Hillshade	250–300	221.62	3.30	3.15	3.15	0.015	0.014	0.014	0.224	0.016
	200–250	89,250.44	259.45	314.87	352.12	0.003	0.004	0.004	−1410	0.003
	150–200	306,686.8	5193.93	6328.9	7562	0.017	0.021	0.025	0.353	0.019
	100–150	85,814.72	475.65	559.81	614.41	0.006	0.007	0.007	−0.764	0.006
	50–100	18,890.39	43.41	50.54	53.17	0.002	0.003	0.003	−1645	0.003
	0–50	1414.38	2.18	2.53	2.71	0.002	0.002	0.002	−2044	0.002
Humidity (%)	75–80	59,071.72	1432.73	1775.39	2442.13	0.024	0.030	0.041	0.712	0.027
	70–75	249,233.66	3745.74	4436.33	5012.9	0.015	0.018	0.020	0.233	0.017
	65–70	171,005.31	745.06	993.69	1051.27	0.004	0.006	0.006	−1005	0.005
	<65	22,967.66	54.39	54.39	81.26	0.002	0.002	0.004	−1615	0.003
Insolation (Hours)	2700–2800	4373.7	74.95	83.46	83.46	0.017	0.019	0.019	0.365	0.019
	2600–2700	149,922.62	2085.83	2603.91	3409.02	0.014	0.017	0.023	0.156	0.015
	2500–2600	123,480.1	919.68	986.32	1051.59	0.007	0.008	0.009	−0.469	0.008
	2400–2500	117,329.61	1419.26	1629.11	1747.50	0.012	0.014	0.015	0.016	0.013
	2300–2400	105,098.18	1478.2	1957.00	2295.99	0.014	0.019	0.022	0.167	0.015
	2200–2300	2074.14	0	0	0	0	0	0	**−0.469 ***	0
Precipitation (mm)	2400–2800	5012.81	35.06	35.06	35.06	0.007	0.007	0.007	−0.532	0.008
	2000–2400	10,286.57	132.26	132.26	131.62	0.013	0.013	0.013	0.077	0.014
	1600–2000	20,541.19	430.63	506.08	531.68	0.021	0.025	0.026	0.566	0.023
	1400–1600	66,379.08	550.95	769.49	916.67	0.008	0.012	0.014	−0.36	0.009
	1200–1400	132,983.26	1623.23	2009.96	2402.33	0.012	0.015	0.018	0.025	0.013
	1000–1200	90,577.8	945.34	1115.63	1311.52	0.01	0.012	0.014	−0.131	0.011
	800–1000	130,193.4	1226.4	1474.78	1642.62	0.009	0.011	0.013	−0.234	0.01
	700–800	39,288.9	677.81	804.97	1048.72	0.017	0.020	0.027	0.371	0.019
	600–700	7015.34	356.24	411.57	567.34	0.051	0.059	0.081	1,451	0.056

Table 2. *Cont.*

Variables	Classes	Total Area (ha)	AS 1990 (ha)	AS 2000 (ha)	AS 2012 (ha)	*CPji* (AS 1990)	*CPji* (AS 2000)	*CPji* (AS 2012)	IV (AS 1990)	FM (AS 1990)
Slope (%)	40–45	175	0	0	0	0	0	0	**−0.967 ***	0
	35–40	874.97	0	0	0	0	0	0	**−0.967 ***	0
	30–35	2670.4	1.35	1.35	1.35	0.001	0.001	0.001	−3159	0.001
	25–30	7100.77	33.55	33.55	33.55	0.005	0.005	0.005	−0.924	0.005
	20–25	16,322.43	61.62	73.16	72.73	0.004	0.004	0.004	−1148	0.004
	15–20	37,573.66	264.08	276.15	290.43	0.007	0.007	0.008	−0.527	0.008
	10–15	79,761.58	360.91	421.9	439.29	0.005	0.005	0.006	−0.967	0.005
	5–10	156,451.83	1267.97	1596.84	1863.89	0.008	0.010	0.012	−0.384	0.009
	0–5	201,347.71	3988.44	4856.85	5886.32	0.020	0.024	0.029	0.509	0.022
Soil	Humic Cambisols	110,548.72	708.37	800.85	819.07	0.006	0.007	0.007	−0.619	0.007
	Rankers	12,992.15	31.48	31.48	31.48	0.002	0.002	0.002	−1592	0.003
	Dystric Cambisols	48,878.67	581.17	829.4	1067.76	0.012	0.017	0.022	−0.001	0.013
	Dystric Fluvisols	3017.1	6.39	6.39	6.39	0.002	0.002	0.002	−1726	0.002
	Eutric Lithosol	187,479.93	1475.36	1776.12	2140.97	0.008	0.009	0.011	−0.414	0.009
	Calcic Cambisols	8275.49	77.74	86.98	86.98	0.009	0.011	0.011	−0.237	0.01
	Calcic Luvisols	34,032.09	1300.16	1509.65	1793.44	0.038	0.044	0.053	1166	0.042
	Hortic Luvisols	40,991.55	320.14	376.3	421.69	0.008	0.009	0.010	−0.421	0.009
	Calcic-chromic Cambisols	13,019.96	169.54	215.53	215.55	0.013	0.017	0.017	0.09	0.014
	Eutric Cambisols	30,585.64	1213.24	1512.2	1792.56	0.04	0.049	0.059	1204	0.044
	Chromic Cambisols	6065.93	80.23	100.8	197.57	0.013	0.017	0.033	0.106	0.015
	Hortic Podzols	6390.79	13.8	13.77	13.77	0.002	0.002	0.002	−1707	0.002
	Eutric Fluvisols	0.33	0.3	0.33	0.33	0.909	1.000	1.000	4336	1000

Table 2. *Cont.*

Variables	Classes	Total Area (ha)	AS 1990 (ha)	AS 2000 (ha)	AS 2012 (ha)	*CPji* (AS 1990)	*CPji* (AS 2000)	*CPji* (AS 2012)	IV (AS 1990)	FM (AS 1990)
Temperature (°C)	16.0–17.5	83,699.31	2360.49	2918.1	3851.4	0.028	0.035	0.046	0.863	0.031
	15.0–16.0	60,518.29	819.04	918.61	929.71	0.014	0.015	0.015	0.129	0.015
	12.5–15.0	135,430.82	977.72	1250.24	1320.63	0.007	0.009	0.010	−0.5	0.008
	10.0–12.5	135,296.25	814.51	994.85	1122.5	0.006	0.007	0.008	−0.682	0.007
	7.5–10.0	72,973.84	935.96	1094.53	1279.85	0.013	0.015	0.018	0.075	0.014
	<7.5	14,359.84	70.2	83.47	83.47	0.005	0.006	0.006	−0.89	0.005
DWBW (km)	5–6	135.23	1.26	11.52	11.52	0.009	0.085	0.085	−0.245	0.01
	4–5	2872.22	140.47	226.48	236.48	0.049	0.079	0.082	1413	0.054
	3–4	24,827.85	458.91	563.72	676.75	0.018	0.023	0.027	0.44	0.02
	2–3	80,622.99	1053.36	1258.36	1404.17	0.013	0.016	0.017	0.093	0.014
	1–2	154,963.46	1443.75	1803.56	2327.76	0.009	0.012	0.015	−0.245	0.01
	0–1	238,856.6	2880.17	3396.16	3930.88	0.012	0.014	0.016	0.013	0.013
TWI	>25	910.24	12.52	10.48	10.43	0.014	0.012	0.011	0.145	0.015
	20–25	2612.17	43.22	47.5	53.52	0.017	0.018	0.020	0.33	0.018
	15–20	18,209.96	297.73	348.24	401.76	0.016	0.019	0.022	0.318	0.018
	10–15	174,288.6	3317.83	4030.44	4772.98	0.019	0.023	0.027	0.47	0.021
	5–10	306,257.38	2306.62	2818.86	3342.93	0.008	0.009	0.011	−0.457	0.008

Note: * These values correspond to the smaller IV observed in the variable under analysis.

5.2. Spatial Variation of the Probability of Artificialization Surfaces in the Zêzere Watershed

The artificialization surface probability is higher in the downstream sector of the watershed, as shown by the maps resulting from application of statistical methods described above (Figure 5).

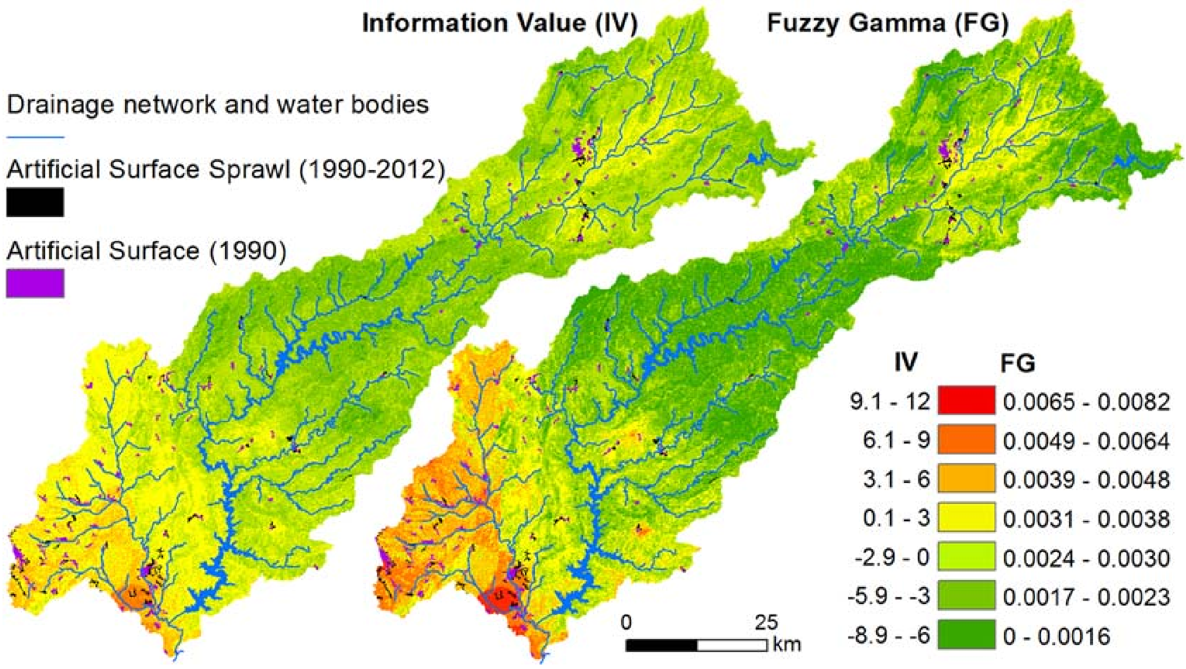

Figure 5. Artificialization surface probability determined by information value and fuzzy gamma, with artificial surfaces from 1990 (the classification of this map follows the method of natural breakdown).

The map with the results of information value shows the sectors upstream and downstream of the watershed, especially this last one, with a high probability of artificialization surface.

The map with the results of the fuzzy gamma operator shows the highest probability in the vicinity of the main water lines in the southwest of the Nabão River, but also shows that the central areas in the upstream sector have some probability of artificialization surface.

The success curve characterizes the quality of a forecast system by describing the system's ability to correctly anticipate the development or non-development of a predefined event [56,57]. In this case, the predefined event is the artificialization of the surfaces in the Zêzere watershed, and the probability of artificialization obtained was validated with the artificial surfaces that have emerged up to 2012. During the validation of results it was found that both models have similar robustness for the determination of artificial surfaces probabilities, as noted through with success rate curves (Figure 6). With around 35% of total area of the watershed classified in descending order of probability of artificialization, about 80% of the artificial surfaces of 2012 are validated, and with about 50% validated, 90% of the total artificialized area (Figure 6). However, modeling using a fuzzy gamma operator presented slightly better results, with AUC of 79.4%, compared to the AUC of 79.1% obtained by the information value.

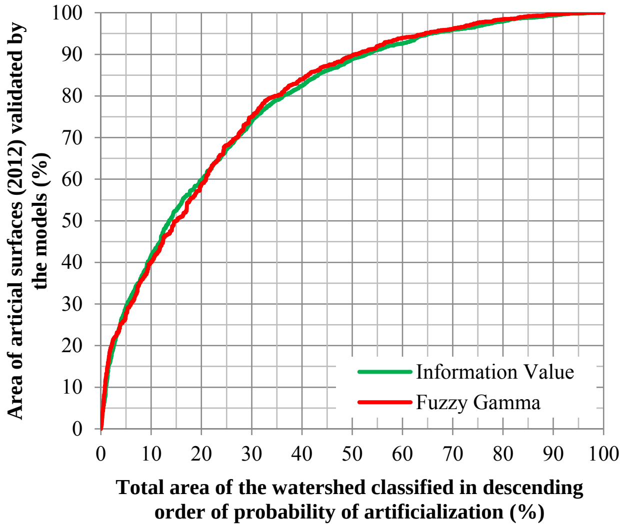

Figure 6. Success rate curve for the statistical models used in the determination of artificial surface probabilities.

5.3. Artificialization Surfaces by the Sectors of the Zêzere Watershed and the Relevance of the Environmental Predisposing Factors to Artificialization Process

The surface artificialization probability is highly variable, spatially, depending on the conditions existing in the territory. The statistical results presented in Table 3 demonstrate high variability of artificialization probability between the sectors defined in the watershed, showing areas A and B with the minimum values, and sector C with maximum probability of artificialization.

Table 3. Statistical description of information value (IV) and fuzzy gamma (FG) by sectors (S) of the Zêzere watershed (significance level $p < 0.05$).

Description	IV			FG		
	S (A)	S (B)	S (C)	S (A)	S (B)	S (C)
Min.	−8.89	−8.89	−4.49	0	0	0.0014
Max.	3.34	4.25	10.41	0.0051	0.0067	0.0082
Mean	−2.58	−1.67	1.88	0.0020	0.0023	0.0041
Std. Dev.	1.84	1.98	1.86	0.0007	0.0008	0.0011

In order to assess the artificialization probability it is also important to know which environmental predisposition factors are the most important. Thus, the accountability and reliability index for each sector of the Zêzere watershed were determined, where the three most relevant predisposition factors in the analysis are highlighted because they contain artificial surfaces in the year 1990 (bold values in Table 4).

The slope turned out to be a very important factor for the artificialization in the three sectors, mainly because of the high area of artificial surfaces in the smaller slope classes. Hillshade is also an important predisposing factor, particularly in sectors B and C. Once sector A includes areas of higher altitude and with a more rugged relief, the humidity and the insolation are the most important factors for the artificialization in this sector; however, the average density of artificial surfaces in each precipitation class is also important considering the set of predisposition factors.

In sector B the temperature has an important influence on surface artificialization, but an analysis of the medium density of artificial surfaces for each independent variable in this sector shows the importance of the type of soils, in particular the Calcic luvisols, where the main drinking water reserves are located.

The C sector soil is also important, considering the high artificialization that occurred in certain classes, but the insolation is an important factor in the analysis of the average density of artificial surfaces by class.

Table 4. Accountability (A_I) and reliability (R_I) indexes by sectors (S) of the Zêzere watershed.

Variables	S (A)		S (B)		S (C)	
	A_I	R_I	A_I	R_I	A_I	R_I
Aspect	59.9	1.0	54.2	0.9	54.5	3.8
Hillshade	72.5	1.1	**91.1**	1.0	**94.6**	3.4
Humidity	**98.5**	1.5	67.5	0.9	44.8	5.0
Insolation	**84.4**	1.5	65.0	1.3	36.8	6.5
Precipitation	44.1	2.2	48.0	1.0	56.4	5.7
Slope	**77.8**	0.9	**69.4**	1.2	**87.2**	3.4
Soil	30.2	1.2	69.3	3.5	**81.3**	3.9
Temperature	47.3	1.6	**86.7**	0.8	74.7	3.6
DWBW	26.9	1.3	54.7	0.8	67.9	3.9
TWI	45.0	1.0	64.2	1.2	70.4	4.0

6. Discussion

The probability of surface artificialization obtained by the information value and fuzzy gamma methods have many similarities in the study area.

These results indicate a good performance of these methods in modeling surface artificialization probabilities, i.e., the artificial surfaces used for modeling (1990) made it possible to differentiate the territory with different probability of artificialization, confirming that a part of these surfaces with a high probability the artificialization occurred (a fact confirmed by overlapping them with the artificial surfaces of 2012). However, it was also found that the new artificial surfaces are located mostly in the periphery of the existing ones, in particular of larger artificial surfaces, which justifies the good performance of the models, i.e., if the expansion occurred mainly from the larger urban centers, it is also more likely that the expansion areas exhibit the same characteristics as the areas of the original urban centers.

The robustness of the methods used has been tested in different studies for determining the susceptibility or probability of occurrence of natural phenomena (e.g., landslides, forest fires, etc.), where the best results have been achieved by the information value model [42]; however, in this research the fuzzy gamma model presented the best performance (Figure 6), although by a marginal difference in relation to the results of the information value model.

The two maps (Figure 5) show that the central sector (B) of the watershed is where there is less probability of artificialization (soils occupied mostly by forest, scrub, and herbaceous vegetation). The natural conditions of this sector are less favorable to human occupation, in particular due to the slope (>25%). This conjugation of less favorable factors to surface artificialization has been referred in some other studies, e.g., Druga and Faltan [58].

The spatial distribution of artificial surfaces in the Zêzere watershed is very uneven throughout the territory and its location is conditioned mostly by the same morphology, this factor being the most important on the distribution of artificial surfaces [58].

The change in the area of artificial surfaces in the Zêzere watershed was evaluated at different times (1990, 2000, 2006, and 2012), which identified the consequences of an increase in the quality of surface water [17,59]. Taking into account the importance of this natural resource and the interference of artificial surfaces in its quality, it is essential to know which areas are those with the greatest artificialization probability in order to avoid new construction, especially in the vicinity of water bodies. These areas are currently experiencing an increase in demand due to the scenic context and watersports, among others [17].

However, in this research it was not proved that the distance to water bodies and watercourses is an important variable in determining the probability of artificial surfaces, because urbanization is still in the process of development in the vicinity of water bodies and infrastructure currently located in these areas is scattered. Additionally, the spatial resolution that characterizes CLC cartography (25 ha) induces limitations to this analysis that require further work. This fact demonstrates the importance of knowledge about the properties of the available GI datasets, and their influence in the results presented in this research that have to be taken into account.

The urban development is also influenced by the location of the main housing clusters [5], which also influence the surface artificialization process, particularly on the periphery of these clusters, where there have been some cases of new housing and infrastructure construction (e.g., roads, railways, industrial complexes, and support equipment, etc.) [3,6]. As a result of this research we highlight the areas with the greatest probability of artificialization (e.g., the SW of sector C), taking into account that under the same environmental conditions which created artificial surfaces in the past, these areas might be artificialized in the future, based on the concept of uniformitarianism implicit in the methodologies used [42,60,61]. Since human intervention was not included in the modeling procedures, and is one of the main agents of LUCC [17,59], some discussion here is justifiable. On the one hand, the application of these variables is impossible, as there are not enough data to demonstrate certain conditions in the past to the watershed under study (e.g., socio-economic power and conditions of the families, infrastructure, or urbanization index, search for housing, or construction of certain infrastructures). On the other hand, there is a very high uncertainty about these human conditions for large periods (next decades), so this approach can only be carried out assuming different kinds of scenarios for the future.

The influence of these man-made factors in the artificialization surface, namely the urbanization in the proximity of road networks, can form the basis of the explanation of the results that are not explained by the models used in this research. However, the option to use only environmental data is due to the fact that the variables used do not present large variations in relatively short periods, such as those considered in this investigation. However, it is acknowledged that this information resulting from anthropic actions is important for determining the areas that will, in the future, become artificial surfaces, but this factor depends only on human actions, such as building new roads or other infrastructure essential to the location of people and goods. Thus, these anthropic actions are encompassed in the process of artificialization and the resulting data are considered artificial surfaces in CLC data.

7. Conclusions

Surfaces artificialization in the Zêzere watershed is more likely to occur in the downstream sector (sub-basin of Nabão River), and this is the place with the highest density of artificial surfaces at present.

The determination of the areas with highest probability of artificialization in the Zêzere watershed, using only environmental data, showed good results, a fact confirmed in the validation (through the curves of success) of the results obtained by the methods of information value and fuzzy gamma.

By comparing the artificialization probability of the sectors delimited in this watershed, it was observed that there is similarity between the results of the two methods obtained for the whole area of the watershed. However, the results differ among sectors, with the highest probability of artificialization in sector C. This spatial differentiation is essential for decision-making in land use planning; in particular, for determining the possible interferences resulting from artificialization in the vicinity of important water bodies to the public water supply. Once there are favorable environmental conditions for this process to occur in these areas, these surfaces present some probability of artificialization. Yet, in this context, it was noted that there are conditions for the increase of the artificialization in the upstream area of the watershed, but the development of this process at this location can be negative in the maintenance of downstream water bodies (water stress). This process leads to important impacts on water quality, mainly due to urban growth in a disorderly manner, and characterized by deficient sewage network systems in the vicinity of the reservoirs.

The spatial differentiation of the artificialization probability will allow better decisions (preventive or reactive) in the territory. In our case it is a watershed with major water bodies in Continental Portugal, and better decisions will contribute to minimize possible consequences resulting from transitions of other types of LUC to artificial surfaces. However, this assessment must include other factors, such as socio-economic conditions [62], restrictions, or obligations set out in territorial and sectorial management plans and programs, along with the chosen strategy to monitor legal framework implementation.

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